Interannual Variability of Vegetation in the United States and its Relation to El Niño/Southern Oscillation

Zuotao Li & Menas Kafatos

Center for Earth Observing and Space Research,
Computational Sciences and Informatics, MS 5C3,
George Mason University, Fairfax, Virginia 22030, USA

Abstract The Normalized Difference Vegetation Index (NDVI) is widely accepted as a good indicator for providing vegetation properties and associated changes for large scale geographic regions. Using multivariate time series data analysis methods based on Principal Component transform and Wavelet Decomposition, a sequence of 11-year monthly Advanced Very High Resolution Radiometer (AVHRR)-derived NDVI data from 1982 to 1992 is examined to study the vegetation and climate variation trends over the United States. We find that one interannual NDVI variation signal over the United States, exhibits a strong relationship with the El Niño/Southern Oscillation (ENSO) Index which is a measure of the phase and amplitude of the Southern Oscillations (SO). The corresponding spatial patterns of NDVI anomaly are also extracted for mapping the possible impacts of ENSO activity. The NDVI anomaly patterns approximately agree with the main documented precipitation and temperature anomaly patterns associated with ENSO, but also show additional patterns not related to ENSO. This study shows that ENSO activity effects may have regionally significant effects for vegetation in the United States.

Key words: NDVI; El Niño/Southern Oscillation; principal component analysis; remote sensing.

1 Introduction

A number of studies have shown that the Normalized Difference Vegetation Index (NDVI), derived by dividing the difference in infrared and red reflectance measurements, as measured by the NOAA-series AVHRR instruments, by their sum, provides an effective measure of photosynthetically active biomass (Justice et al. 1985, Tucker and Sellers 1986). NDVI has also been shown to be well correlated with physical climate variables including rainfall, temperature, and evapotranspiration in a wide range of environmental conditions (Gray and Tapley 1985, Nicholson et al. 1990, Cihlar et al. 1991). NDVI may therefore be considered to represent not only the vegetation response to climate effects but also be a surrogate for such variability for a given region and time. Thus, potential information on climate variation trends may be inferred by extracting the variability patterns from the complex vegetation responses indicated by the NDVI measurements.

The variability of remotely sensed NDVI time series data has been studied in the past in a variety of ways. For example, some previous studies on NDVI variability based on the principal component analysis have identified seasonal trends, satellite and orbital changes effects, and also interannual variability signals including one signal associated with El Niño Southern Oscillation (ENSO) teleconnection effects over Africa (Eastman and Fulk 1993, Anyamba and Eastman 1996). In addition, a significant association between NDVI anomaly over Africa, Australia, and South America and tropical Pacific sea surface temperature anomaly has been reported as well (Myneni, et. al. 1996).

In the present work, a sequence of 11-year monthly AVHRR NDVI derived data, on the "afternoon" NOAA-7,-9,-11 operational satellites, from 1982 to 1992 is examined to study the vegetation response and climate variation trends over the United States. This study was carried out by using George Mason University's Virtual Domain Application Data Center (VDADC) (Kafatos, Li, et al. 1997) data analysis toolkit. This toolkit provides a variety of standardized analysis functions including principal component, time series and wavelet analysis functions.

Here, we identify a number of principal component spatial patterns associated with either expected natural vegetation patterns in the United States or possibly associated with anthropogenic activites. Also, a case is built for identifying one component (the fifth) as associated with ENSO occurences. In the present work, we concentrate on the latter.

Interannual climate anomalies have significant global socio-economic impacts. The El Niño Southern Oscillation is the largest known global climate variability signal on interannual timescales. The links between the regional interannual climate variations and ENSO activities are a major topic of scientific investigation of both the US Global Change Research Program (USGCRP) and NASA (see *SGCRC 1988*).

The Southern Oscillation (SO) consists of two phases. El Niño is the warm sea surface temperature (SST) phase of SO in the central and eastern tropical Pacific; while La Niña is the opposite cool phase. The recurrence of ENSO has a periodicity of approximately 2 to 7 years. The Southern Oscillation Index (SOI), defined as the sea level pressure difference between Darwin and Tahiti is now widely used as an index of the phase and amplitude of the Southern Oscillation (Rasmusson 1985). The El Niño events show large negative SOI deviations, while the La Niña events show positive SOI deviations.

ENSO produces interannual variations in the thermal circulation of the tropics. It also affects the atmospheric circulation and causes regional climate impacts outside the tropics, as far as North America, in shifting the normal precipitation and temperature patterns, the so called "teleconnection" effects (Kinter 1983, Shukla and Wallace 1983, Kang and Lau 1984). Teleconnection effects, which have been recognized as an important extratropical influence of ENSO interannual phenomena, are primarily associated with equatorial sea surface temperature anomalies (SSTA), and include winter hemisphere effects extending to North America (Ropelewski 1992). Moreover, a lot of attention has been focused on effects in the tropics, specifically on the monsoon regions of East Asia, India and Australia. Finally, ENSO influences through SST have been linked to Sahel rainfall (Xue and Shukla 1997), to Zimbabwean drought (Cane et al. 1994) and are in general believed to exert strong influence on interannual climate in various African regions.

Impacts of ENSO activities in the United States have also been reported. For example, the El Niño event of 1982-83 was blamed for devastating coastal storms and mud slides along the southern California coast, flooding in the states bordering the Gulf of Mexico, and drought in the north central states, reducing corn and soybean production. Salmon harvests along the United States Pacific Northwest coast were also down sharply due to reduced coastal upwelling and a general warming of the ocean's water (Glantz 1996). Similar strong effects have also been reported in the most recent El Niño event of 1997-98, the strongest in this century.

2 Data Sets

The NDVI data are global monthly at 1 degree resolution, produced as part of the NOAA/NASA Pathfinder AVHRR Land program and made available by the NASA Goddard Space Flight Distributed Active Archive Center (GDAAC) (NASA Goddard DAAC 1997). These data cover three El Niño events: the strong 1982-1983 event; the 1986-1987 event; and the 1991-1992 event, the latter being part of a more extended ENSO activity in the early 90's. The data used in this analysis is a subset of the global NDVI data set which covers the entire United States. The temporal coverage is 132 months, from January, 1982 to December, 1992.

The spatial and temporal patterns of ENSO activity impacts over the United States can be extracted based on the three most recent El Niño events and also the associated cold phases, such as the 1988-1989 La Niña event. Although the ENSO events of the early 90's appear to be different from the well-defined El Niño events of the 80's, the emphasis of our work is on detecting ENSO-related patterns independently of the exact individual nature of the ENSO events. Although significant volcanic eruptions (e.g. Mt. Pinatubo) during this chosen period and possible linkages with the specific ENSO events have been reported (Handler and Andsager 1994), the issues of correlation between ENSO activities and volcanic eruptions as well as possible impacts on Pathfinder data of such eruptions have not been considered in the present study.

We focus here on finding the interannual NDVI variability patterns at continental scales. The reduction of spatial resolution can reduce topographic and other small scale variability effects and enable a clear detection and description of large scale climate patterns (Rossow and Garder 1984, Anyamba 1994). In our picture, the 1^oX1^o Level 3 data sets are more appropriate than higher resolution (Level 2) data sets and can yield significant scientific information that higher resolution data sets may not be appropriate for.

We use SOI as the indicator of ENSO activities. The SOI data set is also obtained from NASA Goddard DAAC Climatology Interdisciplinary Data Collection and were originally constructed by the Climatic Research Unit at East Anglia University.

3 Analysis Methods

3.1 Seasonal signal removal

To proceed with time scales longer than seasonal, we have removed the strongest seasonal signals from the original NDVI time series data. This process is done by applying a seasonal decomposition method to decompose a time series into a strictly seasonal periodic component and a residual component, and obtain frequency components of variation through a sequence of locally weighted regression smoothing. A detailed description of Local

Regression Models and Locally Weighted Regression Smoothing can be found in Cleveland and Devlin (1988). A backfitting algorithm produces a seasonal component with a period equal to 12 months. The (monthly) subseries of this component are smoothed though time. Then the seasonal component is subtracted from the original time series data. A detailed description of the Seasonal Decomposition procedure can be found in Cleveland et al. (1990).

3.2 Principal Components Analysis (PCA) in the time domain

Like other climatic time series data, the underlying assumption for doing Principal Components Analysis (PCA) in the time domain, is that the NDVI time series data inherently exhibit temporal correlations. Therefore it is possible to transform these time series data into a set of standardized linear combinations (SLC) corresponding to coherent patterns that may be linked to some particular natural or anthropogenic processes.

The principal component analysis algorithm produces a set of SLCs, called the principal components, which are orthogonal to each other and taken together account for all the variance of the original data (Mardia et al. 1979). In general, there are as many principal components as variables. However, it is usually possible to only consider a few of the principal components, which together explain the bulk of the original variations. A detailed review of PCA can be found in Johnson and Wichern (1982) and Emery and Thomson (1998).

The NDVI time series data over the United States can be represented as a data matrix with a column vector corresponding to different location observations at a given time and different columns corresponding to different times. The PCA is carried out in the time domain. Therefore, the derived principal components represent spatial patterns and the associated principal component loadings describe associated temporal characters of these components. The loadings indicate the correlation of each component with members of the original series. In addition, the loadings themselves represent a temporal signal. By comparing the loading signal with one particular climate variation signal (e.g. SOI), the relationship between the associated principal component and this climate signal can then be inferred.

3.3 Extracting Interannual signals with Wavelet Decomposition

Wavelet analysis (Daubechies 1982) is particularly suited for identifying and isolating interested scales of climatic patterns. For example, the wavelet analysis has been applied to study the correlation between two time time series on scales of interest (Bradshaw and McIntosh 1994). It is often superior to the usual Fourier spectral analysis in cases (such as the present one) where non-smooth time series data are present.

Wavelets are fundamental building block functions, analogous to the trigonometric sine and cosine functions, and are localized in time or space. In wavelet analysis, linear combinations of wavelet functions are used to represent a time series signal. Wavelets separate a singal into multiresolution components. The fine and course resolution components capture, respectively, the fine and course scale features in the singnal.

The orthogonal wavelet series approximation to a continuous time series signal $f(t)$ is expressed in terms of:

$$f(t) \approx S_J(t) + D_J(t) + ... + D_1(t)$$

where J is the number of multiresolution components for different time scales.

The functions

$$S_J(t) = \sum_k s_{J,k}\phi_{J,k}(t)$$

and

$$D_J(t) = \sum_k d_{J,k}\psi_{J,k}(t)$$

are called the smooth (low frequency) signal and the detail (high frequency) signals respectively, where the coefficients $s_{J,k}$ and $d_{J,k}$ are the wavelet transform coefficients (k ranges from 1 to the number of coefficients in the specified component) and the functions $\phi_{J,k}(t)$ and $\psi_{J,k}(t)$ are the approximating wavelet functions.

For this study, we try to indentify the correlation between the time series signals: principal component loadings and SOI to infer the possible relationship between the corresponding component patterns and the ENSO varability. Since only interannual time scales are of interest here, the variations over shorter timescales are removed. This procedure is carried out based on the principle of wavelet shrinkage (Donoho and Johnstone 1992). Wavelet shrinkage smoothing algorithms include three steps: (1) Applying the discrete wavelet transform/wavelet decomposition (using the S8 symmlet wavelet); (2) Shrinking the selected wavelet coefficients, which correspond to shorter timescales, to zero; (3) Applying the inverse discrete wavelet transform to obtain the wavelet shrink estimate, which stands for the components of interannual timescales.

4 Results

The first six principal component loadings are shown in Figure 1. We did not take out the first component pattern because we did not want to obtain PCA components based on derived data, instead we show the orignal first five PCA components. We find that the fifth principal component loading is strongly correlated with the SOI signal on interannual timescales. The correlation coefficient of the interannual components (derived by Wavelet decompositions) of the two signals is: $r = 0.67$, $p < 0.001$ (Figure 2). We emphasize that this correlation refers to the entire time series, even through for specific ENSO events the correlation may be stronger or weaker (e.g. there is less of a significant correlation in the 1982-1983 warm event). The fact that the *overall* r is significantly high (0.67) indicates the *general* correlation irrespective of specific events. We have also carried similar correlation analysis for the other five PCA components (namely 1, 2, 3, 4 and 6) and found no significant correlation with SOI. The NDVI anomaly spatial patterns associated with the fifth principal component are shown in Figure 3. These spatial patterns may have a possible relationship with the ENSO activities including both El Niño and La Niña effects for the period of 1982 to 1992.

From the spatial patterns of the fifth component (Figure 3), we identify five anomaly areas, showing comparatively large variations, within the United States: (1) Mexican Gulf states, primarily Texas; (2) Southern High Plains including part of Texas, Oklahoma, Kansas, and Nebraska; (3) Northwest Canada border states, mainly Montana and North Dakota; (4) Eastern Canada, and mainly Maine inside the United States; (5) part of Northeastern states, mainly some areas in West Virginia, Ohio, and Pennsylvania.

Generally speaking, the ENSO activities influence the interannual variability of NDVI by shifting normal precipitation and temperature patterns through teleconnections or direct links. Some climate effects, such as the North Pacific Oscillation (NPO) (Gershunov et. al. 1999), have been proposed as significant factors in how ENSOs affect North American weather. However, in this study, we are showing a possible connection between vegetation variability and ENSO. What climate effects are due to ENSO which they, themselves, might be influencing local vegetations is not our focus here.

The relationship between NDVI and precipitation and temperature is very complex. They are highly dependent on regional effects, such as location, soil and vegetation type. Ropelewski and Halpert (1986) presented the North American precipitation and temperature patterns associated with the ENSO based on station data spanning seven or more ENSO events from 1875 to 1980. They suggested four candidate precipitation anomaly areas: Gulf and Mexican Area (GM), Mid-Atlantic Area (MA), High Plains (HP) and Great Basin (GB), the latter covering the Southwest states; and three candidate temperature anomaly areas associated with ENSO activities: Northwest North America (NNA), Southeast United States (SUS) and Eastern Canada (EC). In Figure 4, we show the precipitation and temperature spatial patterns from Ropelewski & Halpert (1986) (4b) as compared to our fifth PCA component (4a). The spatial patterns of the fifth component patterns (Figure 3 and Figure 4a) approximately agree with the precipitation and temperature anomaly patterns except for GB. One possible explanation is the very low vegetation coverage of this region – primarily shrublands. From a strong correlation between the fifth component (loadings) and SOI as well as its associated spatial patterns, we suggest a possible relationship between the fifth component and ENSO activities. Other significant correlations have been found for cultivated land production (corn yield in the USA) on smaller spatial scales (Handler 1990).

We have attempted to identify the nature of the other first few principal components. The percentage of explained variances for the first five principal components is shown in Table 1, where we summarize the properties of the other vegetation patterns studied here as well. Note that the low percentage variance (0.3%) of component 5 is relative to component 1 (as are components 2, 3 and 4, as well). Component 5 is not insignficant when compared to the other components, 2, 3 and 4.

Parameter Pattern	*Distinct Region Affected*	*Principal Component*	*% of variance explained*	*Relevant Timescales*	*Origin*	*Comment*
NDVI[1]	*i)* Texas and Mexican Gulf States *ii)* Texas, Oklahoma, Kansas, Nebraska *iii)* Montana, North Dakota *iv)* Maine (also Eastern Canada) *v)* West Virginia, Ohio, Pennsylvania	**5**	0.3%	4-5 years (ENSO timescales)	ENSO	Region *v)* shows positive anomaly, the other four show negative anomalies
NDVI[1]	Continental	**1**	94.2%	N/A	Natural Vegetation Patterns	
NDVI[1]	Continental	**2**	0.6%	N/A	North/South Temperature Differentiation	
NDVI[1]	Northeastern states, Great Lakes area and Eastern Canada	**3**	0.5%	> decade?	Anthropogenic? (Industrial)	
NDVI[1]	Midwest farming area	**4**	0.4%	> decade?	Anthropogenic? (Farming)	
Precipitation[2]	Gulf and Mexican area; High Plains; Mid-Atlantic area; Great Basin (SW States)	N/A	N/A	ENSO timescales	ENSO	Roughly agrees with NDVI Pattern
Temperature[2]	SE US; NW North America; Eastern Canada	N/A	N/A	ENSO timescales	ENSO	

Table 1

1. This Work. 2. Ropelewski & Halpert (1986)

Inspection of the time series pattern for component 1 loadings (Figure 1, upper left panel) indicates what appears to be a general increasing trend until 1990. This is not though a statistically significant long-term trend. Moreover, inspection of the corresponding spatial pattern indicates that component 1 (Figure 5) differentiates NDVI between the mountainous and low precipitation regions west of the Rockies from lower-level, vegetated regions east of the Rockies and it actually more or less matches the land cover (classes) map of North America (North America Land Cover Characteristics Database 1996). The line of differentiation runs roughly north to south along the eastern border of the Rockies in the mountain states, extending north to the Canadian Rockies and South to Mexico. Time series patterns for component 2-4 loadings (Figure 1, upper right panel and middle panels) show no obvious temporal behavior. Inspection of the spatial pattern for component 2 (Figure 5, upper right panel), indicates a line of demarcation that straddles the 40^o parallel of latitude, except for the Midwest region between roughly 100^o W to 85^o W of longitude. It is likely that it represents a north to south temperature differentiation and it indeed roughly matches a demarcation for average dates of first killing frost in the fall (Edward 1995). The spatial pattern for component 3 (Figure 5, lower left panel) shows a negative anomaly for the Northeastern states and the Great Lakes area as well as Eastern Canada, and we tentatively identify it with what might be industrial activity in Northeast United States. Although our time coverage is short compared to long-term climate change timescales, this pattern matches GCM simulations of CO_2 doubling and the Mapped Atmosphere-Plant-Soil System (MAPSS) (MAPSS Model 1997). We cannot, however, be certain that this is not fortuitous. Finally, component 4 shows a negative anomaly for the Midwest farming areas (Figure 5, lower right panel). It is conceivable that both components 3 and 4 are associated with anthropogenic effects on vegetation and, if confirmed, would be of ecological significance. Anyamba and Eastman (1996), on the other hand, identified two components as related to orbital changes in the satellite platforms as well as the change from NOAA-9 to NOAA-11 in Nov. 1988. Although this remains a possibility here, we cannot make a similar statement because we find no obvious trend after Nov. 1988 in the time series of all PCA components. Component 5 is, of course, identified here as related to the ENSO phenomenon discussed above. Even though the significance of the fifth component explained variance may appear small, if it were significantly higher (say at levels greater than 1%), there would be dramatic ecosystem effects which are obviously not observed. Neverthless, the effect is not zero. It remains to be further explored, what the ecological implications of the ENSO signal found here are for North American ecosystems.

Since the first component corresponds to large-scale (i.e. many degrees) natural vegetation patterns (low NDVI versus high NDVI and geophysical location east or west of the mountainous regions) and is not associated with either climate or anthropogenic effects (i.e. climatological pattern), the next four components are significant and of similar weight. Components 3 and 4 need, however, to be correlated with some known anthropogenic signals (such as aerosol emissions or estimates of acid rain deposition) in order to establish their connection to industrial activity or farming. There may be other explanations and our suggestion of possible anthropogenic effects needs to be thoroughly investigated. The fifth component (associated with climate ENSO variabilities), on the other hand, is significant because a high correlation has been established with ENSO signals (SOI and previously known precipitation patterns associated with ENSO activities). It counts for 5.2% of total vegetation variance when the variation corresponding to vegetation type and geophysical location which is, of course, the primary variance, is excluded.

5 Conclusions

In conclusion, this study has illustrated the interannual variability of vegetation, revealed in NDVI variation patterns. We find that one NDVI variation signal, namely the fifth component, exhibits a possible relationship on the interannual time scales, with the El Nino/Southern Oscillation Index. The corresponding spatial patterns are also extracted.

These NDVI anomaly patterns approximately agree with documented precipitation and temperature anomaly patterns associated with ENSO activities, but also reveal new patterns not detected previously in these climatological variables. More research is needed to clearly identify that one component is related to ENSO as well as the nature of the other components and whether some of them are related to anthropogenic effects.

The variability of NDVI may serve as a good proxy for climate variations and thus can provide insights into understanding regional climate effects of ENSO teleconnections. Similar methods may also be applied to other countries or areas outside the United States. However, the phenomenon of ENSO impacts on the regional climate outside of the tropics is very elusive and actual teleconnection patterns may vary for different ENSO episodes. It is extremely interesting that for North America and particularly the United States, ENSO teleconnections reveal themselves not only in precipitation and temperature patterns but also in biosphere vegetation patterns. The present study shows that the ENSO activity impacts the biosphere which may potentially have regionally significant effects for vegetation in the United States.

Acknowledgements

We acknowledge useful input from Drs. R. Yang, W.J. Emery and Ms. C. Lim and partial support from NASA cooperative agreement with the Global Change Data Center at Goddard Space Flight Center (NCC 5-143) and the NASA Earth Science Information Partners program (NCC 5-306).

References

Anyamba, A. "Retrieval of ENSO Signal from Vegetation Index Data", *The Earth Observer*, **6**, 24-26 (1994).

Anyamba, A. and Eastman J.R. "Interannual variability of NDVI over Africa and its relation to El Niño/Southern Oscillation", *International Journal of Remote Sensing*, **17**, 2533-2548 (1996).

Bradshaw G.A. and McIntosh, B.A. "Detecting climate-induced change using wavelet analysis", *Environmental Pollution*, **83**, 135-142 (1994).

Cane, M.A., Eshel, G. & Buckland, R.W. "Forecasting Zimbabwean Maize yield using Eastern Equatorial SST", *Nature*, **370**, 204-205 (1994).

Cihlar, J., St.Laurent, L., and Dyer, J.A. "The relation between normalized difference vegetation index and eccological variables", *Remote Sensing of Environment*, **35**, 279-298 (1991).

Cleveland, W.S. and Devlin, S.J. "Locally-weighted Regression: An Approach to Regression Analysis by Local Fitting", *J. Am. Statist. Assoc.*, **83**, 596-610 (1988).

Cleveland, R.B., Cleveland, W.S., Mcrae, J.E. and Terpening, I. "STL: A Seasonal-Trend Decomposition Procedure Based on Loess", *Journal of Official Statistics*, **6**, 3-73 (1990).

Daubechies, I. *Ten Lectures on Wavelets* (SIAM, Philadelphia, 1982).

Donoho, D. and Johnstone, I. "Adapting to Unknown Smoothness via Wavelet Shrinkage", Technical report, Department of Statistics, (Stanford University, 1992).

Eastman, J.R. and Fulk, M.A. "Time series analysis of remotely sensed data using standardized principal components analysis", *Proceeding of the 25th International Symposium on Remote Sensing and Global Environmental Change, Graz, Austria*, **1**, 1485-1496 (1993).

Edward, B.E. Jr.(ed.) *Goode's World Atlas*, 69, (Rand McNally & Company, 1995).

Emery, W.J. and R.E. Thomson, *Data analysis methods in physical oceanography*, Pergamon Press (1998).

Gershunov, A., Barnett, T.P. & Cayan D.R. "North Pacific Interdecadal Oscillation Seen as Factor in ENSO-Related North American Climate Anomalies", *EOS, Transactions, American Geophysical Union*, **V.80, 3,** 25-30 (1999).

Glantz, M.H. *Current of Change: El Nino's impact on climate and society* (Cambridge University Press, 1996).

Gray, T.I., and Tapley, D.B. "Vegetation health: Nature's Climate Monitor", *Advances in Space Research*, **5**, 371-377 (1985).

Handler, P., "USA Corn Yields, the El Nino and Agricultural Drought: 1967-1988", *International Journal of Climatology*, **10**, 819-828 (1990).

Handler, P. and Andsager, K. "El Nino, Volcanism and Global Climate", *Human Ecology*, **10**, 819-828 (1990).

Johnson, R.A. and Wichern, D.W. *Applied Multivariate Statistical Analysis* (Prentice-Hall, 1982).

Justice, C.O., Townshend, J.R.G., Holben, B.N. and Tucker, C.J. "Analysis of the phenology of global vegetation using meteorological satellite data", *International Journal of Remote Sensing*, **6**, 1271-1318 (1985).

Kafatos, M., Li, Z. Yang, R.X.S. Wang, X.S., et al. "The Virtual Domain Application Data Center: Serving Interdisciplinary Earth Scientists", *Proceedings of Ninth International Meeting on Scientific and Statistical Database Management.* IEEE (1997).

Kang, I.N., and Lau, N.C. "Principal Modes of Atmospheric Variability in Model Atmospheres with and without SST Forcing in the Tropical Pacific", *J.Atmos. Sci.* **43**, 2719-2735.

Kinter, J.L. *Barotropic Studies of Stationary Extratropical Anomalies in the Troposphere*, Ph.D. Thesis, Princeton University (1983).

MAPSS Model, “http://www.cgd.ucar.edu/vemap/abstracts/ MAPSS.html”, 1997.

Mardia K.V., Kent,J.T. and Bibby, J.M. *Multivariate Analysis* (Academic Press, London, 1979).

Myneni, R.B., Los, S.O. and Tucker, C.J. ”Satellite-based identification of linked vegetation index and sea surface temperature anomaly areas from 1982-1990 for Africa, Australia and South America”, *Geophysical Research Letters*, **23**, 727-732, 1996.

NASA Goddard DAAC Climatology Interdisciplinary Data Collection, “http://daac.gsfc.nasa.gov/” (1997).

Nicholson, S.E., Davenport, M.L., and Malo, A.R. ”A comparison of vegetation response to rainfall in the Sahel and East Africa using normalized difference vegetation index from NOAA-AVHRR”, *Climate Change*, **17**, 209-241 (1990).

North America Land Cover Characteristics Database, “http://edcwww.cr.usgs.gov/”, U.S. Geological Survey - National Mapping Information (1996).

Rasmusson, E.M. ”El Nino and Variation in climate”, *American Scientist*, **73**, 168-177 (1985).

Ropelewski, C.F. and M.S. Halpert ”North American Precipitation and Temperature Patterns Associated with the El Nino/Southern Oscillation (ENSO)”, *Monthly Weather Review*, **114**, 2352-2363 (1986).

Ropelewski, C.F. "Predicting El Niño Events", *Nature*, **356**, 476-477 (1992).

Rossow, W.B. and Garder, L. "Selection of a map-grid for data analysis and archival", *Journal of Climate and Applied Meteorology*, **23**, 1253-1257 (1984).

SGCRC, *Our Changing Planet*, A Report by the Subcommittee on Global Change Research, Committee on Environment and Natural Resources of the National Science and Technology Council, The FY 1999 U.S. Global Change Research Program.

Shukla, J. and Wallace, J.M. "Numerical Simulation of the Atmospheric Response to Equatorial Pacific Sea Surface Temperature Anomalies", *J.Atmos. Sci.* **40**, 1613-1630 (1983).

Tucker, C.J., and Seller, P.J. "Satellite remote sensing of primary production", *International Journal of Remote Sensing*, **7**, 1133-1135 (1986).

Xue, Y. and Shukla, J. "Model Simulation of the Influence of Global SST Anomalies on the Sahel Rainfall", COLA Preprint, **41** (1997).